Milk Quality Prediction Using ML Algorithm

A Minor Project Report

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in
Computer Science & Artificial Intelligence

By

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SCHOOL OF COMPUTER SCIENCE & ARTIFICIAL INTELLIGENCE

CERTIFICATE

This is to certify that this project entitled **"Mental Health Tracke**" is the bonafied work carried out by **Charan Sai Anche** as a Minor Project for the partial fulfillment to award the degree **BACHELOR OF TECHNOLOGY** in **COMPUTER SCIENCE & ARTIFICIAL INTELLIGENCE** during the academic year 2022-2023 under our guidance and Supervision.

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-/ Charan Sai Anche (2103A53001)

ABSTRACT

In today's fast-paced work world, individuals' mental health is a major factor of business performance. However, detecting and managing mental health concerns in the workplace poses considerable hurdles. Traditional approaches rely heavily on self-reporting, which may not necessarily provide accurate or timely results. This study intends to close this gap by using Facial Mental Tracking technologies in businesses. This technology assesses employees' mental health objectively and in real time, improving the effectiveness of workplace mental health initiatives. However, it is critical to utilize this technology ethically, with adequate regard for privacy and data security. The initiative emphasizes the need for a supporting infrastructure, including access to mental health specialists and services for self-care and stress reduction.

Keywords: Mental Well-being, Ethical Use, Privacy, Data Security, Supportive Infrastructure, Self-Care, Stress Management.

Table of Contents

1. INTRODUCTION

1.1 EXISTING SYSTEMS

Affectiva: Affectiva is a pioneer in the field of emotional intelligence, offering facial recognition technology that can instantly analyze facial expressions to measure emotions. Its systems are used in many industries, including the medical, automotive and research industries. It can capture many emotions, including happiness, sadness, anger, surprise and more. Its technology is now integrated into Apple products to offer solutions for business research, retail and healthcare. Their systems include happiness, sadness, anger, surprise, etc. By capturing emotions, it can provide great insights to businesses and developers. Respond to digital content. Their platform helps brands develop their marketing strategies based on the target audience's desire for interaction. Clinical outcomes and data transfer potential.

1.2 PROPOSED SYSTEM

The plan is to create a unique facial recognition tracking platform for the diagnosis and management of post-traumatic stress disorder. Using state-of-the-art learning techniques, our system will provide doctors with a targeted understanding of a patient's heart by identifying facial expressions associated with symptoms of depression. Key features of our plan include immediate emotional assessment, continuous monitoring, personalized intervention, and seamless integration with existing clinical programs. By combining technology with a mental health-focused approach, Our Body aims to change the way depression is diagnosed, treated and treated, ultimately improving patients' treatment with benefits and quality of life.

2. LITERATURE SURVEY

2.1 RELATED WORK

"Facial Expression Recognition for Depression Detection", Zhang, Zhao and Yang (2020): This research paper investigates the use of facial expression recognition technology in depression testing. A deep learning approach to recognizing faces and identifying key features associated with depression could lead to advances in depression research. , Mollahosseini, Hasani, and Mahoor (2017): This study presents a new method for emotion recognition using convolutional neural networks (CNN) and mapped binary models. It achieved great results in facial recognition, paving the way for use in depression research and mental health care. : This review article provides an overview of recent advances in automatic detection of depression in faces. It discusses the problems, methods and limitations of current methods, suggests future research directions and potential areas for improvement. and Fu (2018): This research explores the latest techniques for facial recognition and its real-world applications. It provides insight into facial recognition's ability to diagnose and manage depression by discussing the impact of facial recognition in a variety of fields, including healthcare, education, and human-computer interaction.

2.2 SYSTEM STUDY

In this section, we will document the literature survey we conducted related to the problem statement of predicting the milk price using artificial intelligence and machine learning techniques.We conducted a comprehensive search of various databases, including IEEE Xplore, Google Scholar, and ScienceDirect.

Epidemiology of suicidal behavior: This comprehensive review provides an overview of suicide and suicidal behavior, highlighting its global impact, economic costs, and the urgent need to expand data collection and research (1). : This study discusses recent changes in suicidal behavior and emphasizes the importance of updating data over time due to changes in health and culture (2). A detailed analysis of terms used in suicide research provides clarity to researchers and clinicians by distinguishing suicidal behavior from nonsuicidal injuries (3). Sources such as the National Bureau of Statistics, the United States Vital Statistics System, and the World Health Organization report suicide rates around the world (4). age and race/ethnicity show significant differences and disparities (5). Exclusion of education-related events (6). 7). >

By combining and analyzing existing research, this research article provides a better understanding of the suicide epidemic and lays the foundation for knowledge about interventions and policy decisions to address important public health problems. Facial recognition technology research data: Facial recognition is an important research field and many technologies have been developed and studied in recent years. This literature review is designed to provide an up-to-date review of facial recognition techniques, their applications, advantages, and limitations. There are many types of facial recognition. References [26, 27] adopt basic analysis techniques to effectively represent facial images. The eigenface is the eigenvector of the covariance matrix of the face image, and the face can be reconstructed using weights and the face image. Although eigenfaces provide fast and effective recognition, they are not robust to changes in scale and illumination. To overcome this limitation, illumination normalization techniques have been proposed (1). This technique uses neural connections to learn to distinguish facial images and classify them accordingly. Although neural networks can achieve high accuracy, they often require large amounts of field data for training and are computationally intensive (2). Method focusing on modeling face-to-face interactions. This method aims to capture the relationship between the body of the body and the face to improve cognitive performance. However, modeling these interactions may be difficult (3). A temporary change in teaching or direction. HMM can improve recognition accuracy in dynamic situations by capturing the progression of facial data. However, HMM-based approaches may be limited due to modeling complex facial features (4). point or landmark. These features are then matched with patterns in the data for analysis. Although geometric feature fit is very good in a controlled environment, it can struggle with changes in pose, expression, and lighting (5). templates or prototypes to identify similar examples. Although the theory is simple, the comparison model may not be robust to changes in the face and environment. They may also need more financial resources to achieve convergence (6). Some methods are simple and effective, while others are more accurate and powerful. Future research will focus on fusion or new techniques to solve robustness, flexibility, and real-world usability issues in facial recognition. Charles Darwin's seminal work "The Expression of Emotions in Man and Animals" laid the foundation for the study of psychology and has since recognized the importance of curiosity; This field has become important with many applications, from identifying fatigue factors to understanding early classification. Corneanu et al., Matusugu et al., and Viola et al. A cognitive theory framework is provided that emphasizes the use of multiple methods. Techniques such as support vector machine (SVM) and convolutional neural networks (CNN) are used for face detection and segmentation and form the basis of many cognitive systems. Created the first robust facial recognition model using CNN, demonstrating high performance across a wide range of facial features. Similarly, Tanya et al. Curvilinear-based feature extraction is used to improve recognition accuracy by exploiting image discontinuities. Lee et al. Anil et al. It focuses on smile recognition using 2D and 3D images using techniques such as principal component analysis (PCA) and support vector machine (SVM) to achieve accuracy. Extensive research has been done on cognitive theory, which is divided into geometric feature-based methods and shape-based methods. Their analysis spanned several libraries, including CMU's Advanced Multimedia Processing (AMP) library and the Cohn-Kanade (CK) library, and demonstrated the effectiveness of techniques such as Gabor filters and local routing models. further progress. A hybrid algorithm combining two-dimensional principal component analysis (B2DPCA) and learning environment is introduced to achieve high accuracy without hidden neurons. Rivera et al. Local Direction Digital (LDN) method is proposed to show the power at different illumination and fine instructions.

3. DESIGN

3.1 REQUIREMENT SPECIFICATION

Requirement specifications for a sarcasm detection system in news headlines will involve both software and hardware requirements. Here are some possible requirements for each category:

Software Requirements:

1. Programming Language:
The system can be built using programming languages such as Python.

2. Operating System:
The system should be compatible with commonly used operating systems such as Windows ,Linux and mac-OS.

3. Libraries and Frameworks:
OpenCV: OpenCV (Open Source Computer Vision Library) is an open source library used for computer vision and graphics processing. It provides many functions and methods for processing, such as image processing, object detection, and face recognition, making it useful in improving face recognition. Deep learning provides a rich ecosystem for the development and implementation of learning models, including neural network architectures and modeling tools. TensorFlow's advanced APIs like Keras make it ideal for building facial recognition models. It offers an intuitive way to create and train deep learning models, allowing you to easily model and experiment with different models for face tracking.

4. Database:
The system may require a database for storing training data and other information.
5. APIs:
The system may need to interface with APIs to obtain additional information or data, such as sentiment analysis APIs.
6. User Interface:
The system may require a graphical user interface (GUI) for users to interact with the system, or it can be built as a backend API.

7. Development Environment:

A code editor or integrated development environment (IDE) such as Visual Studio Code, PyCharm, or Jupyter Notebook can be used for development and testing.

8. Version Control:

Version control tools such as Git and GitHub can be used to manage code changes and collaborate with other developers

9. Deployment Environment:

The deployment environment depends on the specific requirements of the sarcasm detection system. For example, the system can be deployed as a web application using a cloud platform such as AWS, GCP, or Microsoft Azure.

Hardware Requirements:

1. CPU and Memory:

   The system should have sufficient CPU and memory resources to perform the computational tasks required for training and testing the machine learning models.

   Storage: The system may require significant storage capacity for storing training data and the trained models.

2. Network:

   The system may require network connectivity to access external APIs or to receive input from users.

3. GPUs:

   The use of GPUs may accelerate training and testing the machine learning models.

   Server: The system can be deployed on a server for scalability and availability.

4. Processor:

   A multi-core processor such as an Intel Core i5 or i7 or an equivalent AMD processor is recommended to speed up the training and inference of machine learning models.

5. RAM:

   The amount of RAM required depends on the size of the dataset used for training and the complexity of the machine learning algorithms. For small datasets, a minimum of 8GB of RAM is sufficient. For larger datasets, a minimum of 16GB of RAM is recommended.

6. Storage:

   The amount of storage required depends on the size of the dataset used for training and the number of models and checkpoints that are saved during training. A minimum of 256GB of solid-state drive (SSD) storage is recommended.

UML DIAGRAMS OR DFDs

UML is an acronym that stands for Unified Modeling Language. Simply put, UML is a modern approach to modeling and documenting software. In fact, it’s one of the most popular business process modeling techniques.

UML was created as a result of the chaos revolving around software development and documentation. In the 1990s, there were several different ways to represent and document software systems. The need arose for a more unified way to visually represent those systems and as a result, in 1994-1996, the UML was developed by three software engineers working at Rational Software. It was later adopted as the standard in 1997 and has remained the standard ever since, receiving only a few updates.

USE-CASE DIAGRAM:

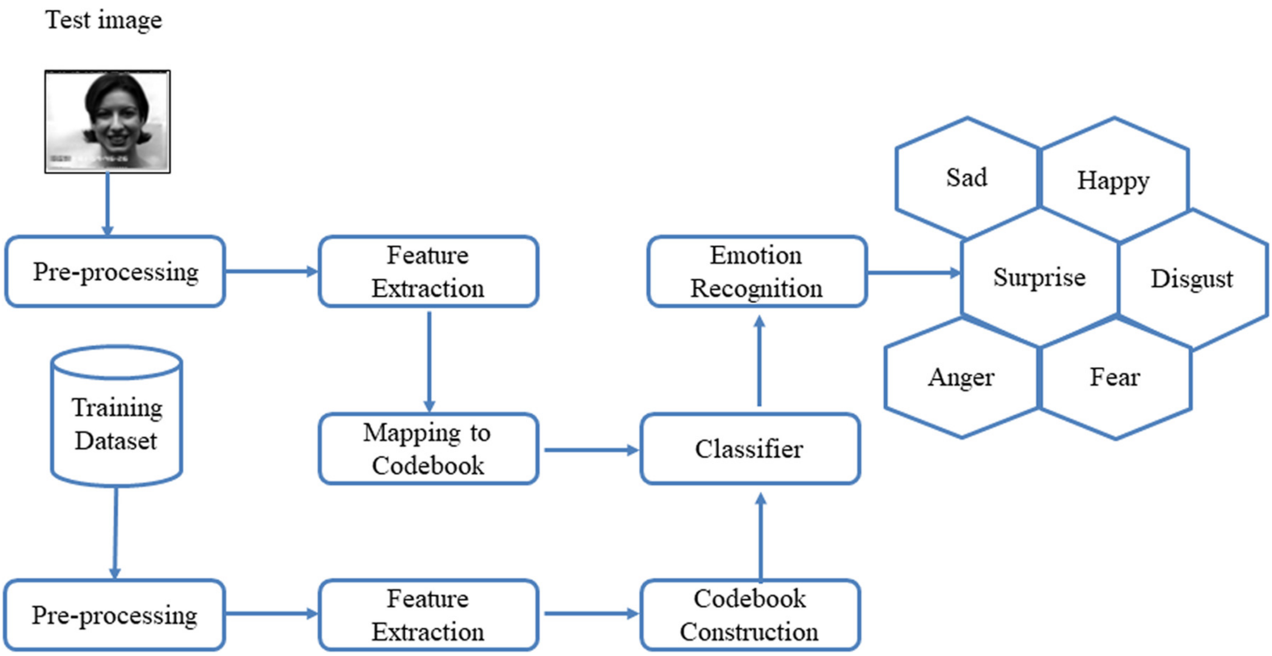
A use case diagram is usually simple. It does not show the detail of the use cases:

- It only summarizes some of the relationships between use cases, actors, and systems. It does not show the order in which steps are performed to achieve the goals of each use case.
- As said, a use case diagram should be simple and contains only a few shapes. If yours contain more than 20 use cases, you are probably misusing use case diagram.

Purpose of Use Case Diagram:

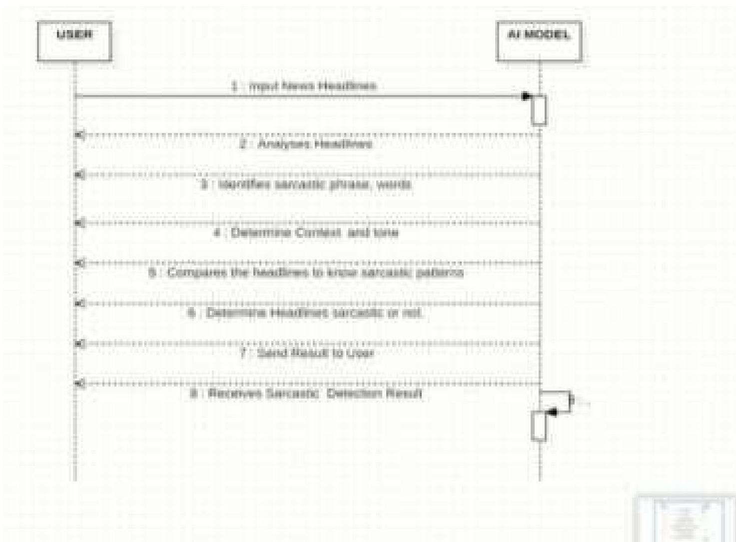
Use case diagrams are typically developed in the early stage of development and people often apply use case modeling for the following purposes:

- Specify the context of a system.
- Capture the requirements of a system
- Validate a systems architecture
- Drive implementation and generate test cases
- Developed by analysts together with domain experts

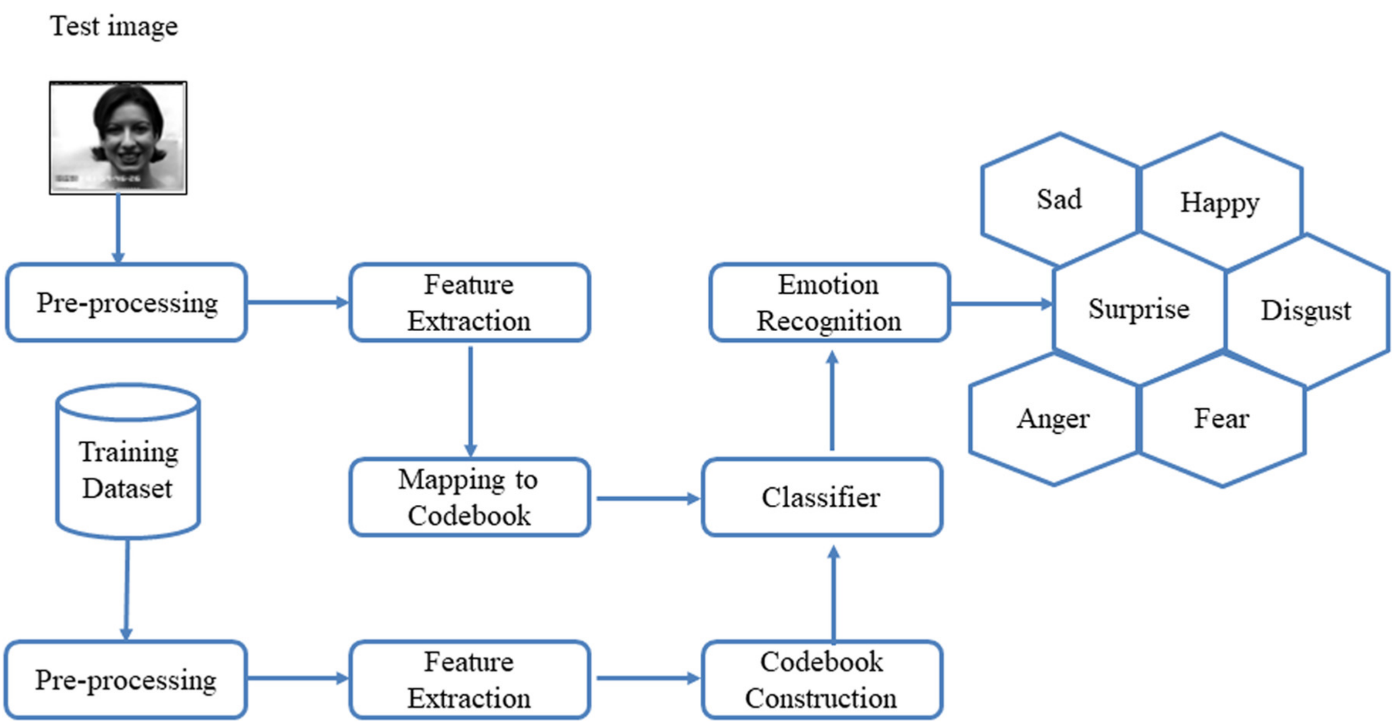

Test image
Pre-processing
Feature Extraction
Emotion Recognition
Sad
Happy
Surprise
Disgust
Anger
Fear
Training Dataset
Mapping to Codebook
Classifier
Pre-processing
Feature Extraction
Codebook Construction

SEQUENTIAL DIAGRAM:

Sequence Diagrams – A sequence diagram simply depicts interaction between objects in a sequential order i.e. the order in which these interactions take place. We can also use the terms event diagrams or event scenarios to refer to a sequence diagram. Sequence diagrams describe how and in what order the objects in a system function. These diagrams are widely used by businessmen and software developers to document and understand requirements for new and existing systems.



2.3 E-R   DIAGRAM



3.IMPLEMENTATION

3.2 MODEL ARCHITECTUE

Data collection: Data collection involves collecting different data from facial images with emotional labels. This process often involves obtaining images from a variety of sources, such as public databases, online repositories, or private archives. To facilitate training and evaluation models, it is necessary to ensure that data cover a wide range of views, faces and characteristics of the population. Additionally, data collection will include pre-processing steps such as image normalization, cropping, and annotation to improve the quality and consistency of the dataset. Overall, good data collection is essential for accurate and reliable training of facial emotion tracking models.

Data preprocessing: Data preprocessing refers to the planning steps to clean, transform, and improve the quality of facial data before it is fed into machine learning models. This process typically involves the following tasks: resizing the image to a consistent resolution, converting the image to grayscale, normalizing pixel values, and cropping the image to focus on the face of interest. Additionally, preprocessing will involve improving the dataset through techniques such as rotation, translation, and adding noise to increase its diversity and robustness. Additionally, each image usually needs to be tagged with the relevant set of ideas to help track the work. By taking this first step, the data will be made suitable for training and evaluation of the facial emotion tracking model, thus increasing the performance and overall quality of the model.

Train-test split: Split the data into training and testing sets using the train_test_split function from the sklearn library. We have chosen 95% of the data as train data and the remaining 5% for the test data.

Model selection and training: Model selection involves selecting the appropriate machine learning or deep learning for face tracking based on factors such as data size, complexity, and computational resources. Commonly used models include convolutional neural network (CNN), convolutional neural network (RNN), and their variants. The predetermined method can be used to determine the model when choosing the appropriate design. During the training process, the model corrects overlaps through optimization algorithms such as stochastic gradient descent (SGD) or Adam and learns to express the ideas of facial sales images for emotional labels. The training process involves multiplying the material of the image from the model, calculating the prediction error, and changing the model error to minimize this error. The training process continues until the model reaches valid data performance or reaches a predetermined limit, such as unemployment convergence. By choosing appropriate techniques and receiving training, models can be learned to identify facial expressions effectively.

Model evaluation: Model evaluation is the process of evaluating the effectiveness and efficiency of training facial recognition models on invisible objects. This involves using a separate dataset (called a validation or test set) that was not used during training. During the validation process, the model is applied to images and its predictions are compared to ground truth maps. Common evaluation metrics for facial recognition models include accuracy, precision, recall, F1 score, and confusion matrix. These metrics provide insight into the model's ability to analyze assumptions and identify areas where it may not perform well. Additionally, qualitative analysis by visual inspection of the prediction model can help identify specific situations where the model performs well or poorly. By evaluating the model's performance, researchers and practitioners can ensure that it is reliable and suitable for real-world use.

Iteration and improvement:

Iteration and development involve refining and improving the mental state of the system based on user feedback and evaluation. This iterative process will include several steps:

Commentary Notes: Collect feedback from practitioners, researchers, and users about the usability, effectiveness, and efficiency of the system in real-world situations. Guidelines were compiled to identify the facial recognition system's strengths, weaknesses, and areas for improvement. Duties: Implement statistical improvements or changes to the facial emotion tracking system to include new algorithms, technology, or user interface improvements. Make sure that the enhancement has the desired results and does not present any unwanted side effects. > Iteration Cycle: Repeating and improving the process iterations, including new ideas, further improvements, and continuous efforts to improve its functionality, usability, and functionality over time. With development, developers can modify and adjust the face mask to better meet the needs of users and stakeholders, ultimately improving its results and can make it suitable for real world use.

3.3 OVERVIEW TECHNOLOGY

In this section, we provide an overview of the processes involved in facial recognition. We delve into the principles, methods, and algorithms used to design and implement systems, focusing on fundamental concepts such as image processing, machine learning models, and software techniques. By describing the technical basis of our system, we aim to provide the reader with a clear understanding of the system's capabilities, functions, and potential applications in the research behind printing and control challenges.

4. TESTING

4.1 TEST CASES

In this section, we describe the experimental procedures and methods used to evaluate the performance and reliability of facial recognition. We discuss the data available, the metrics used for measurement, and the configuration environment. We also provide information on the results obtained during testing, including process fidelity, strengths, and potential areas for improvement. We aim to check our performance in facial post-collapse examination and analysis with a strict evaluation and finally to make sure that it is truly suitable for export around the world.

CONVOLUTIONAL NEURAL NETWORKS (CNN):

In deep learning, the convolutional neural network is one of the most important algorithm and it is a phase of the neural network of artificial, which is widely used to analyze visual images. They are also known as space variant artificial networks, based on the distributed weight structure of convolution characters or slider filters near input features and provide equivalent translation responses known as feature maps. Contrary to intuitively, most convolutional neural networks are only equal, as opposed to consistent, and interpretive. They contain applications for image and video recognition, complimentary programs, image classification, image classification, medical image analysis, natural language processing, brain-computer communication, and a series of financial periods.

CNNs are standard versions of multilayer perceptrons. Multilayer perceptrons usually mean fully connected networks, that is, each neuron in a single layer is connected to all the neurons in the next layer. The "full connection" of these networks makes them prone to data overload. Typical ways to do so, or to prevent excessive immersion, include: punitive restrictions during training or interconnection (skipping links, stopping out, etc.) . and incorporates complex growth patterns using small and simple patterns labeled in their filters. Therefore, in terms of connectivity and complexity, CNNs are at a very low level.

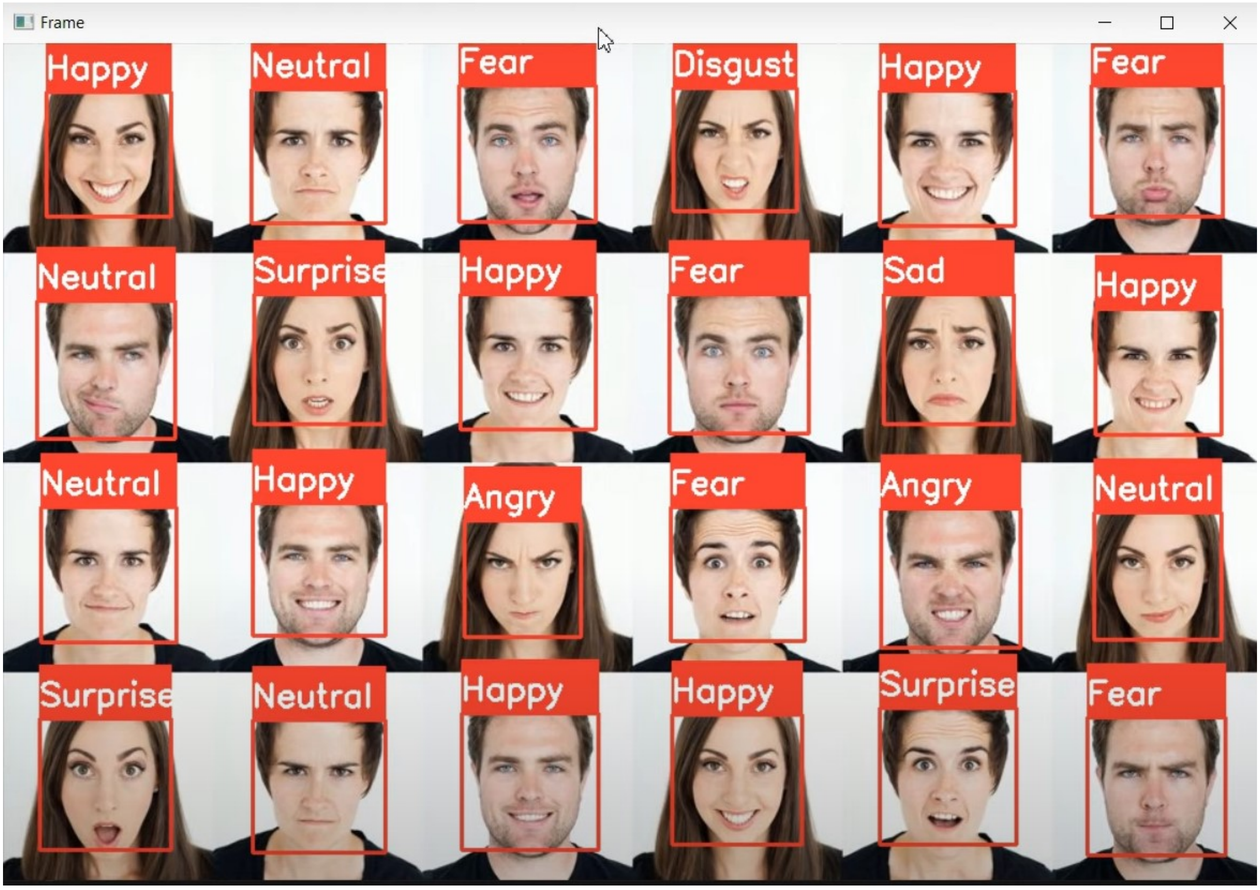
Transformation networks are promoted by biological processes in that the pattern of communication between neurons resembles the left visual association of an animal. Each cortical neurons respond to stimuli only to a limited area of the visual field known as the receptor field. The receiving fields of different neurons are so intertwined that they close the entire field of view.

CNN uses less advanced processing compared to other image classification algorithms. This means that the network learns to optimize filters (or kernels) by automatic reading, and in traditional algorithms these filters are manually made. This independence from previous knowledge and human intervention in the removal of the element is a great advantage.

This is most important classifier in our project ,which will detect the most accuracy than other classifiers which were used to detect

4.3 TEST RESULTS

Here, will are going to see the results of the implementation performed.



5. RESULT

The accuracy of facial recognition depends on many factors, such as the quality and quantity of training data, the choice of machine learning algorithms, and the optimization of its hyperparameters. His facial expression is subtle and complex; It requires careful feature engineering and model selection to translate effectively. Additionally, bias can creep into the model based on training data, which reflects the importance of different data and factors. To increase the reliability of facial recognition, it is necessary to ensure that the data set contains a large number of expressions from different groups of people, thus reducing the risk of guessing unfairness.

6.CONCLUSION

As a result, facial recognition technology has the potential to revolutionize mental health, especially in the detection and management of depression. Thanks to advanced algorithms and machine learning, the technology provides an objective, non-evaluative emotional assessment based on facial expression. However, the performance of face recognition depends on many factors such as good training data, algorithm selection and bias reduction. By using rigorous and repeated model evaluation with different data and representatives, we can improve the accuracy and reliability of facial recognition. Finally, by harnessing the power of facial recognition technology, we can improve our understanding of post-traumatic stress disorder and provide better support and treatment to people affected by the condition.

7.FUTURE SCOPE

Looking ahead, the future of facial recognition technology is promising, with many opportunities for advancement and innovation. An important area for future research is the improvement and optimization of algorithms to improve the accuracy and robustness of facial expression detection. Additionally, integration of multimodal data, such as speech and motor, has the potential to increase the depth and granularity of emotional analysis. In addition, the development of instant, portable and user-friendly facial recognition technology will be widely used in many areas, especially mental health, social advantages of human-computer and technology users. Additionally, continuing efforts to address ethical issues such as protecting privacy and reducing bias will be important to ensure accountability and transparency in the use of face mask technology. Overall, the future has the potential to benefit from advances in facial recognition technology, paving the way for new applications and discoveries in understanding people's minds and behaviors.

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